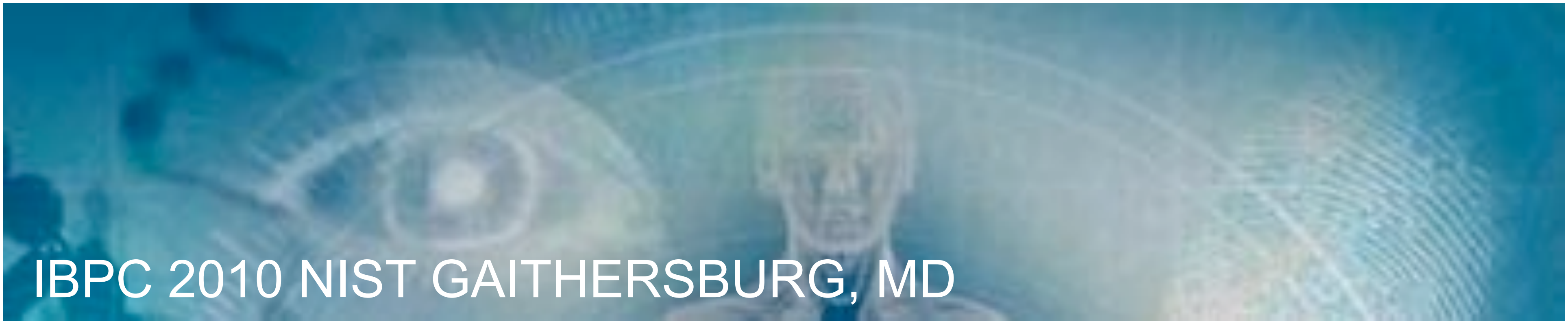

Biometric Covariate Analysis using Partial Area Under Curve

Valorie S. Valencia, PhD

President & CEO, Authenti-Corp

Research Professor of Optical Sciences
University of Arizona

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Collaborative Effort

Valorie Valencia — Authenti-Corp

Matthew Kupinski — College of Optical Sciences, The University of Arizona

Elham Tabassi — National Institute of Standards and Technology, U.S. Department of Commerce

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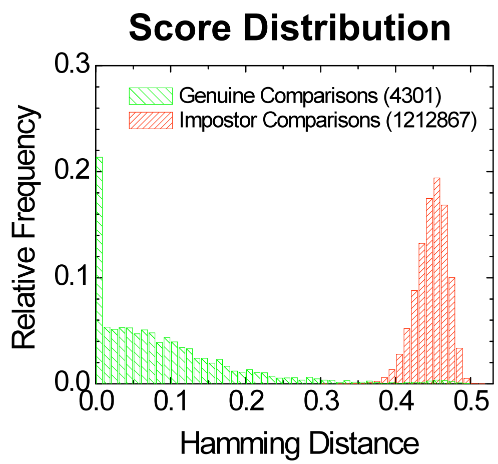
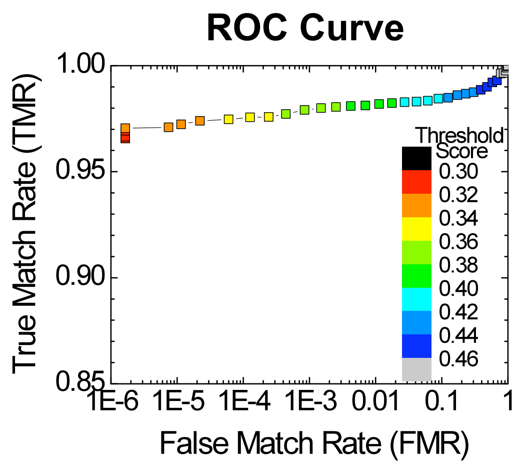
Why perform covariate analysis?

- It is important to understand the influence of various factors (covariates), such as image quality metrics, population demographic factors and environmental conditions on the performance of biometric recognition systems
- This knowledge can profoundly influence how biometric systems are designed and implemented in real-world operational scenarios
- To demonstrate our Area-Under-Curve method for performing covariate analyses, we explore matching performance for three iris datasets from Authenti-Corp's IRIS06 study using the Daugman 2007 algorithm

Covariate Analysis Challenges

- Biometric systems are used for many different types of applications, which necessarily operate at different points on an ROC curve.
  - For example, for admission to Disney World, the higher false match rates associated with lower false non-match rates (higher true match rates) would be tolerable
    - Convenience to the customer is more important than some level of monetary loss
  - At a high-security facility, the lower true match rates associated with lower false match rates would be required
    - Security is more important than convenience.
- The influence of covariates is typically analyzed at one or multiple operating points
  - For example, FMR=10^{-3}, 10^{-4}, 10^{-5} or Threshold Score=0.32, 0.34, 0.36 (Hamming distance)
  - Analysis at multiple points can be difficult, time consuming and cumbersome
  - Results can be difficult to convey and understand

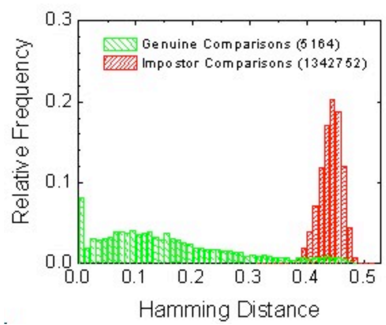




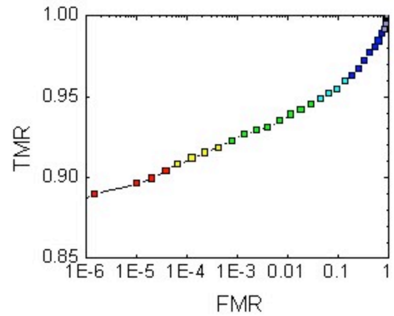
- It is desirable to perform a generalized covariate analysis that is independent of threshold ⇨ Area Under ROC Curve (AUC)

Why use Area Under Curve (AUC)?

Score Distribution



ROC Curve



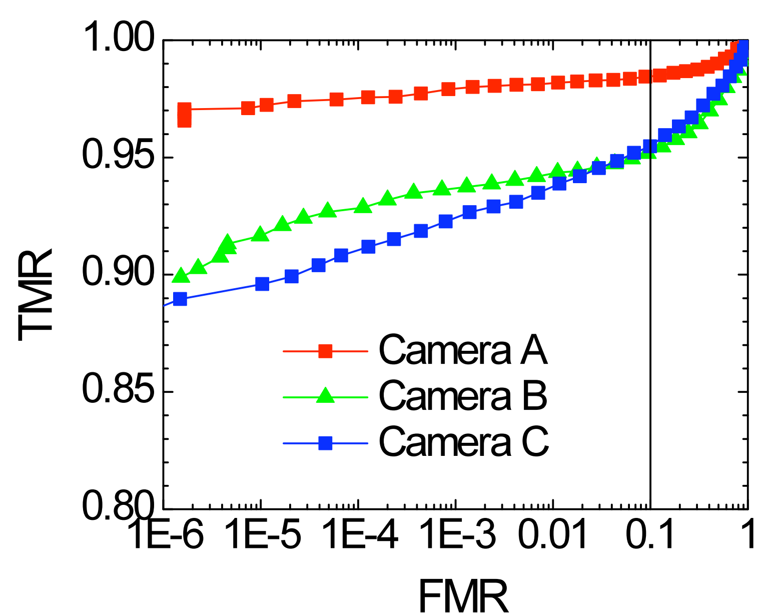
AUC

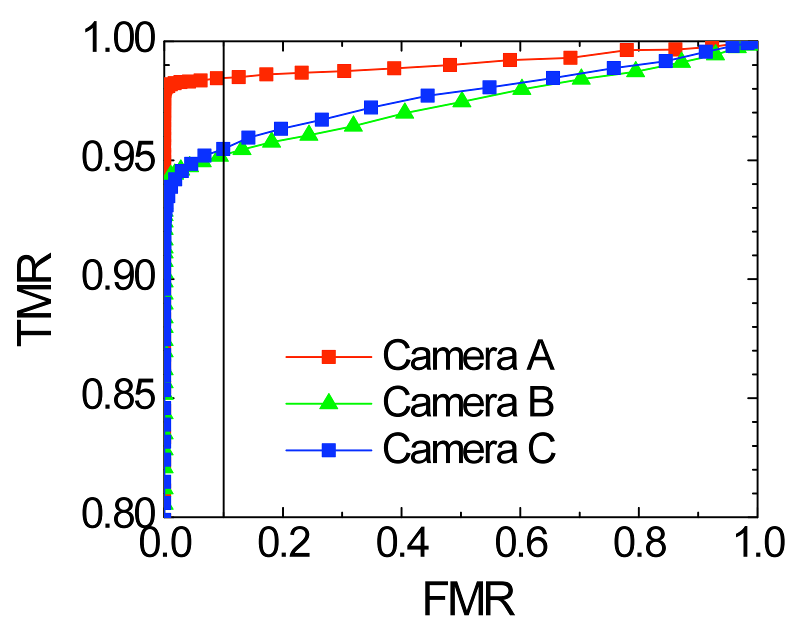
0.9763

- Easy to understand
  - Represents the probability of a correct decision given a genuine image and an impostor image
  - Overall probability of a correct answer
  - The larger the AUC value, the better the overall performance of the system
    - AUC=1 is perfect performance
- Serves as a single figure of merit that characterizes the performance of the system
  - Threshold independent
  - Accounts for all thresholds
- The statistical properties of AUC are well characterized
  - Determining statistical significance of AUC differences straightforward using Wilcoxon estimate
- The analysis space is reduced from a multi-point ROC curve to a single metric
  - The influence of various covariates on system performance can be systematically studied as a function of the AUC figure of merit

Limitations of AUC

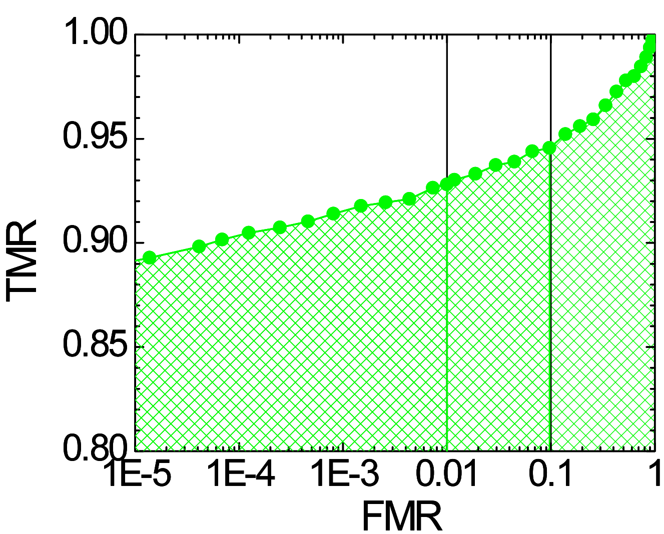
- Single metric from an inherently multi-objective problem
  - While problem is simplified, nuances may be overlooked
- AUC is heavily weighted by portions of the ROC curve where systems most certainly will not operate, that is at false match rates above a certain value, for example, FMR>0.1%

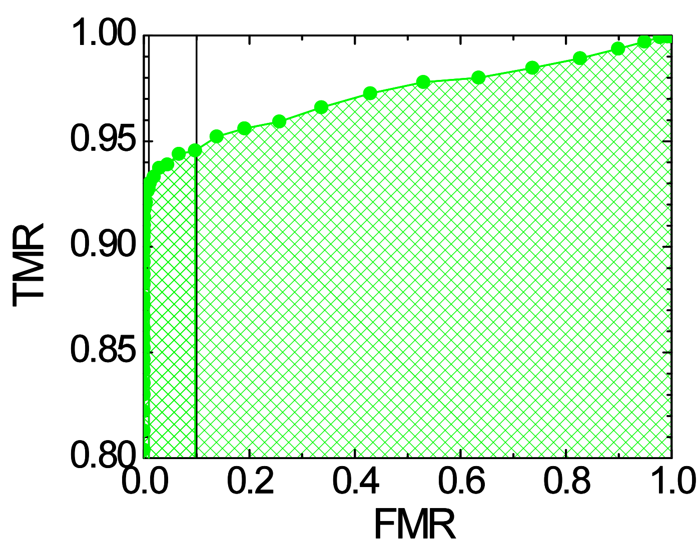




Partial AUC (p-AUC)

- To address limitations of AUC, we propose to look at partial AUC (p-AUC), which is restricted to a range of false match rates that are operationally feasible
- Selecting the range of the ROC curve that is operationally relevant depends upon the modality and scenario
  - For facial recognition, we have seen implementations that operate successfully at false match rates as high as 10%
  - For single-fingerprint systems, acceptable false match rates might be at or below 10^{-3}
  - For iris recognition, operational false match rates below 10^{-4} are typical





Area Under Curve
(probability of correct decision)

FMR ≤ 1.0, AUC=0.972292

FMR ≤ 0.1, p-AUC=0.093847

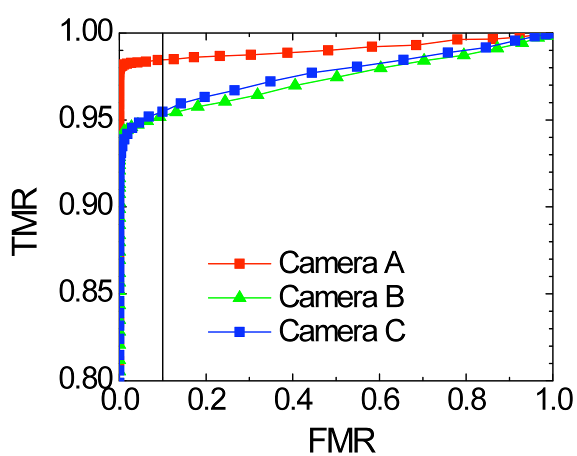
FMR≤0.01, p-AUC= 0.009219

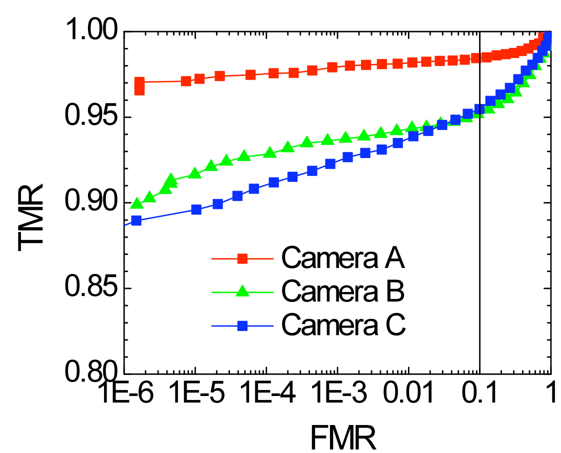
AUC Statistical Analysis

- Need error bars to draw conclusions
- Borrow image assessment approach from radiology
  - Probabilistic Multiple Reader, Multiple Case (MRMC) model
    - Normal cells ⇨ Genuine scores
    - Abnormal cells ⇨ Impostor scores
  - References
    - E. Clarkson, M. A. Kupinski, and H. H. Barrett, “A probabilistic model for the MRMC method. Part 1: Theoretical development”, *Acad. Radiol*., 13:1410-1421, 2006.
    - M. A. Kupinski, E. Clarkson, and H. H. Barrett, “A probabilistic model for the MRMC method. Part 2: Validation and applications”, *Acad. Radiol.*, 13:1422-1430, 2006.

Statistical Properties of AUC & p-AUC

- Variance $(\widehat{AUC})$ = $\sigma^2 = \dfrac{\alpha_1}{N_{gen}} + \dfrac{\alpha_2}{N_{imp}} + \dfrac{\alpha_3}{N_{gen}N_{imp}}$
  - Can directly compute each alpha term and predict variance from genuine and impostor scores
  - Third term accounts for correlations between impostors and genuines
  - OneShot freeware application computes α terms without resampling techniques and is unbiased http://www.radiology.arizona.edu/CGRI/IQ/page2/page7/page7.html
  - Methods and software extended to account for p-AUC





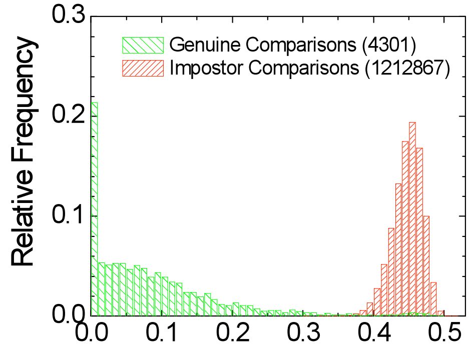
Statistical Significance "p-value"

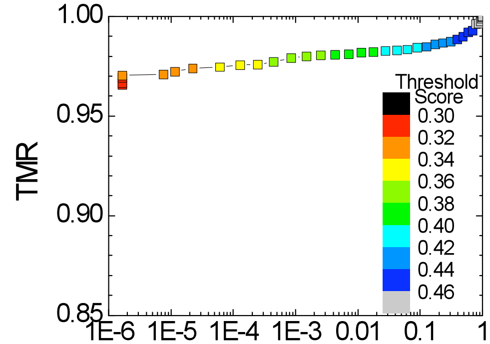
- Use Wilcoxon signed-rank statistical hypothesis test to determine statistical significance between two AUC values
- Non-parametric equivalent to t-test
- Assume null hypothesis ⇨ two AUCs equal
- p-value is the probability that the null hypothesis explains the result
  - Computed from the variances of the two AUCs
  - Small p-value (e.g., $p<0.05$) indicates a significant difference between the AUC values and thus a statistically significant performance difference between the two cases under investigation
- To perform the significance test for partial AUC, we assume that partial AUC is normally distributed
  - Normal assumption has been shown to be valid for as few as 10 subjects (i.e., 10 x 10 matrix of scores)
- Caution
  - p-value indicates statistical significance
  - p-value does not indicate that the hypothesis is correct

p-value Illustration

Score Distributions | ROC Curves | AUC ± σ

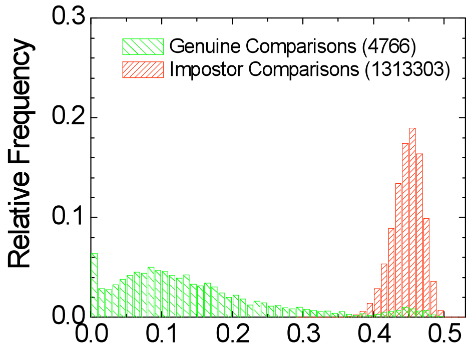
Camera A

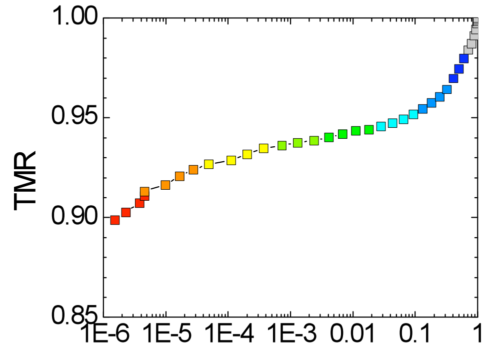




0.9905 ± 0.0012

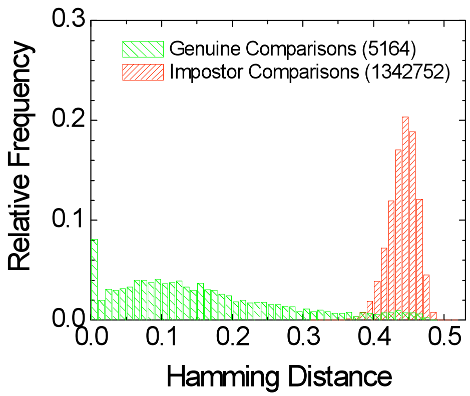
Camera B

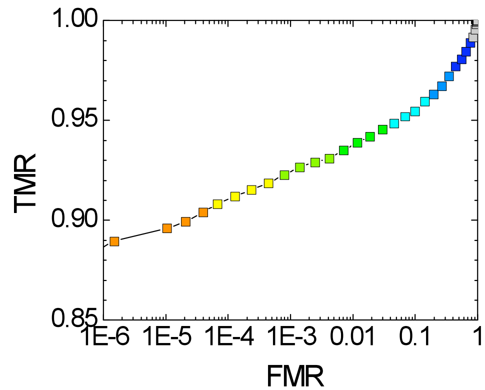




0.9730 ± 0.0018

Camera C





0.9763 ± 0.0016

Calculating p-value

Distribution of Measured AUC Difference (assuming true difference is 0) $= \dfrac{1}{\sqrt{2\pi\sigma_\Delta^2}} \exp\left[\dfrac{-1}{2\sigma_\Delta^2} x^2\right]$

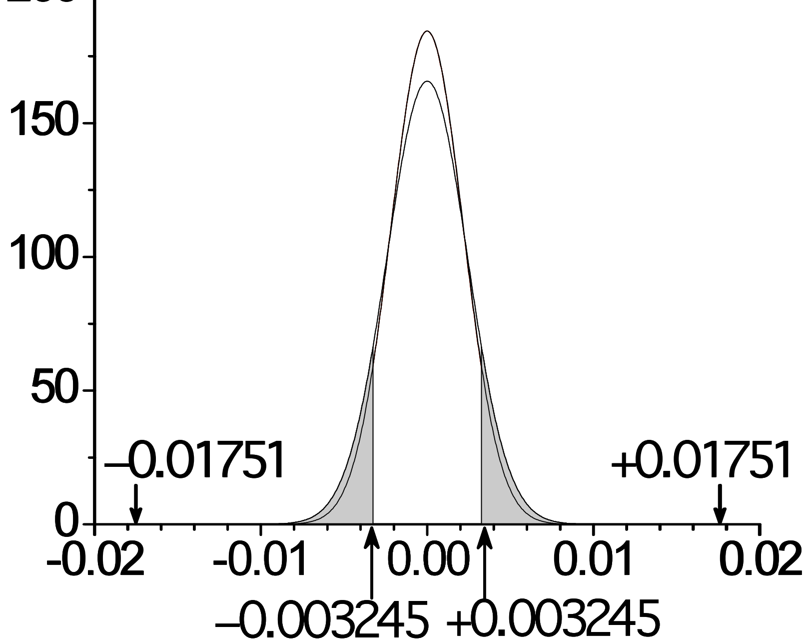
$$\Delta = |AUC_1 - AUC_2|$$

$$\sigma_\Delta^2 = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12}$$

$\Delta_{\text{Camera B-Camera C}} = 0.003245$, $p = 0.1897$ Not statistically significant

$\Delta_{\text{Camera A-Camera B}} = 0.01751$, $p = 0.0000$ Statistically significant

Is the measured AUC difference unlikely?



Distribution of Measured AUC Difference
(assuming true difference is zero)

Integral form:

$$p = 2\int_{\Delta}^{\infty} \frac{1}{\sqrt{2\pi\sigma_\Delta^2}} \exp\left[\frac{-1}{2\sigma_\Delta^2} x^2\right] dx$$

Numerical form:

$$p = 2\left[\frac{1}{2} - \frac{1}{2}\mathrm{erf}\left(\Delta/\sqrt{2\sigma_\Delta^2}\right)\right]$$

probability of measuring observed difference if Δ=0

GLMM Covariate Analysis Approach

- Generalized Linear Mixed Effect model is used to relate probability of verification to subject and image covariates
  - Ross Beveridge's group at Colorado State University
- Pros:
  - Uses empirical performance and covariate data associated with people and imagery to fit a model relating covariate values to probability that a person will be correctly verified
  - Model quantifies how changes in covariates alter the probability that a person will be correctly verified
- Cons:
  - GLMM modeling complex
  - Requires parameter tuning
  - Performed at a selected operating point on the ROC, i.e., FMR=0.001

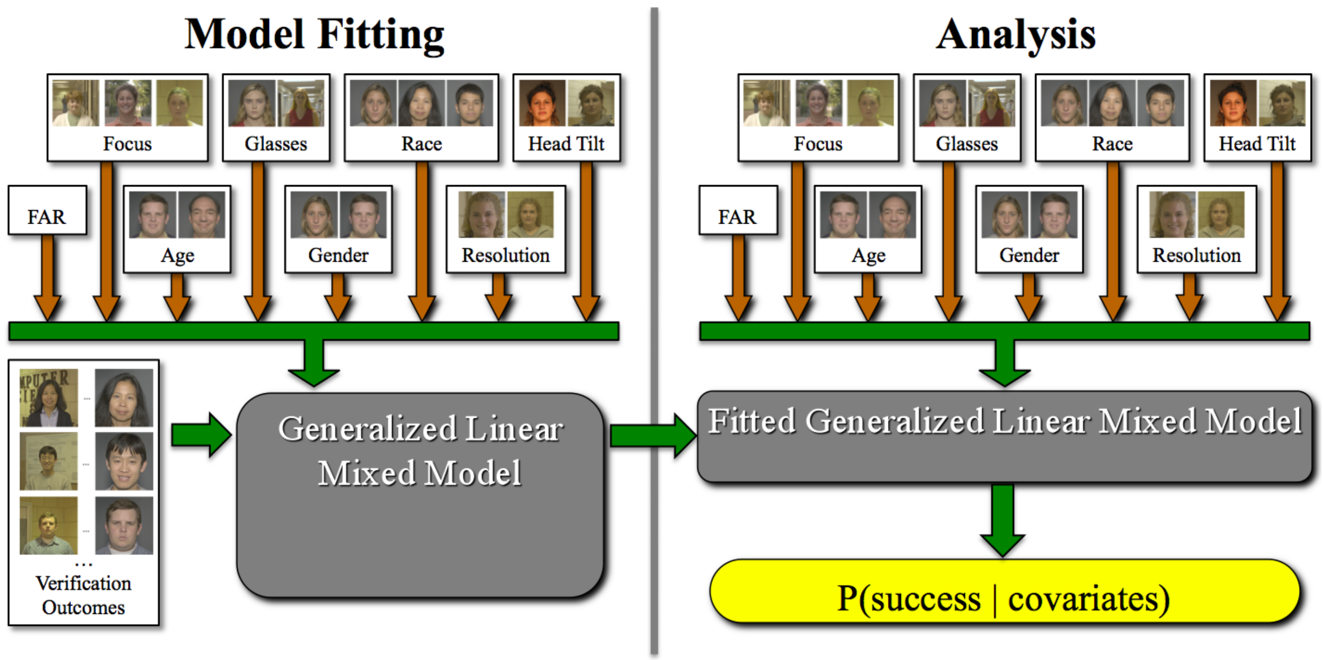


Figure from Beveridge, *et. al*., "Focus on Quality, Predicting FRVT 2006 Performance," 2008 8th IEEE International Conference on Automatic Face and Gesture Recognition

AUC Covariate Analysis Approach

- To demonstrate utility of AUC & p-AUC figures of merit and Wilcoxon signed-rank statistical hypothesis test, we evaluate the influence of three covariates on iris recognition performance:
  – Camera
    - A, B & C
  – Gender
    - Male & Female
  – Eye
    - Left & Right

AUC & p-value Nomenclature

Camera

		A	B	C
	AUC	0.9905	0.9730	0.9763
A	0.9905		← p=0.0000	← p=0.0000
B	0.9730	↑ p=0.0000		↑ p=0.1897
C	0.9763	↑ p=0.0001	← p=0.1897	

probability of correct decision

- Camera A: 99%
- Camera B: 97%
- Camera C: 98%

p-value legend

← ↑ p>0.05, Not Statistically Signficiant

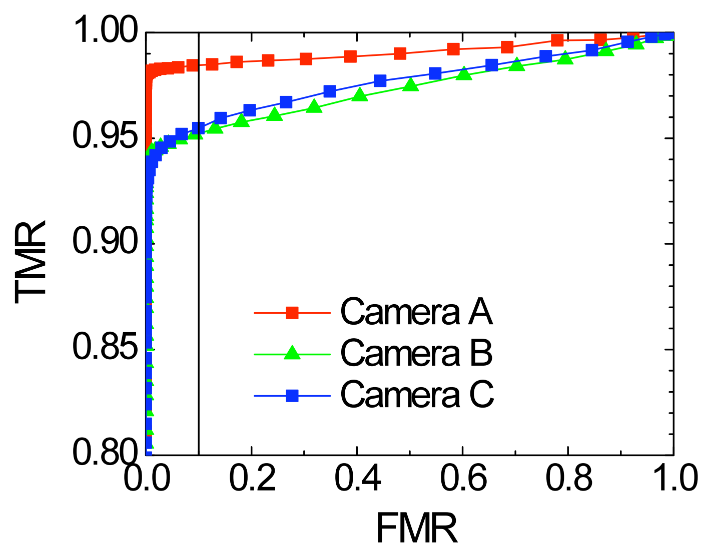
← ↑ $p \leq 0.05$, Statistically Significant

Direction of arrow indicates higher AUC value

Cameras A, B & C

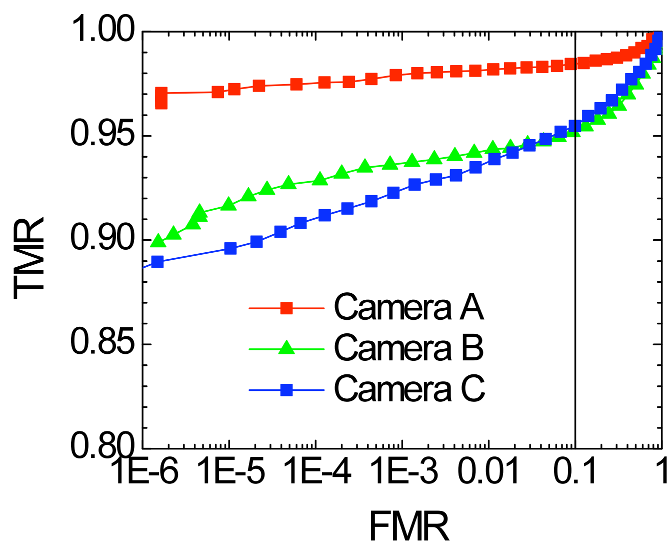
FMR ≤ 1.0

		A	B	C
	AUC	0.9905	0.9730	0.9763
A	0.9905		← p=0.0000	← p=0.0000
B	0.9730	↑ p=0.0000		↑ p=0.1897
C	0.9763	↑ p=0.0001	← p=0.1897	



FMR ≤ 0.1

		A	B	C
	p-AUC	0.0983	0.0948	0.0947
A	0.0983		← p=0.0000	← p=0.0000
B	0.0948	↑ p=0.0000		← p=0.7852
C	0.0947	↑ p=0.0001	↑ p=0.7852	



- Camera A performs significantly better than Cameras B & C
- Camera C performs better than Camera B for AUC (FMR≤1.0) but Camera B performs better than Camera C for p-AUC (FMR≤0.1)
  – ROC curves cross

Gender – Cameras A, B & C Combined

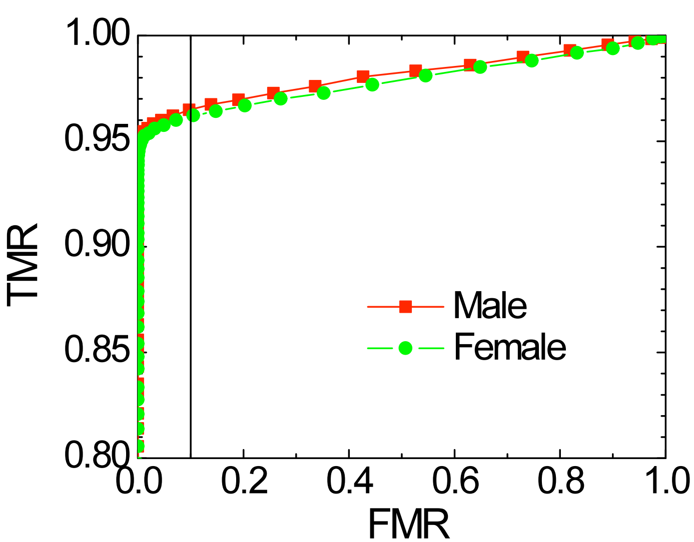
FMR ≤ 1.0

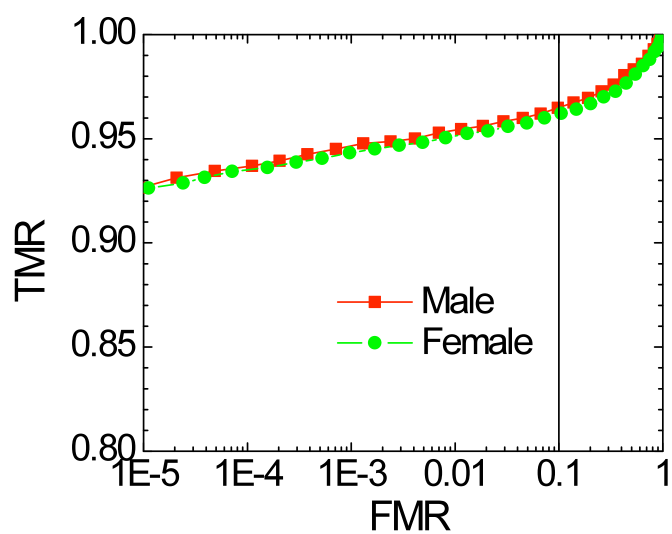
	AUC	Male	Female
	AUC	0.9814	0.9809
Male	0.9814		← p=0.1801
Female	0.9809	↑ p=0.1801	

FMR ≤ 0.1

	p-AUC	Male	Female
	p-AUC	0.0960	0.0957
Male	0.0960		← p=0.1897
Female	0.0957	↑ p=0.1897	

For Cameras A, B & C combined, there is no significant performance difference between men and women





Gender – Camera A

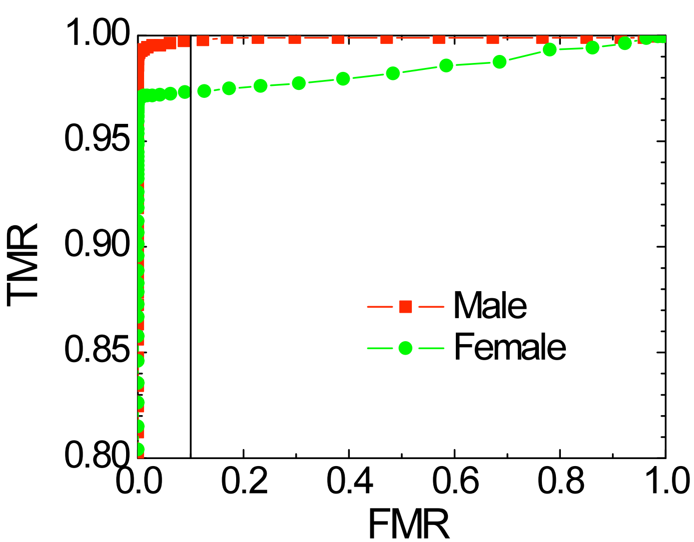
FMR ≤ 1.0

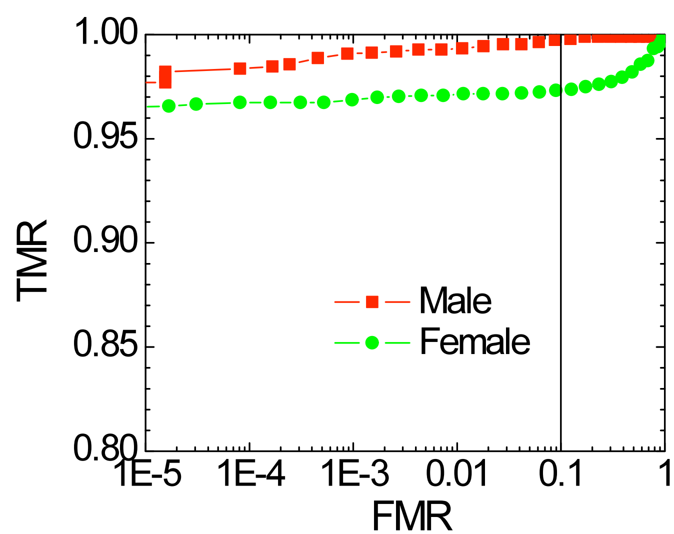
		Male	Female
	AUC	0.9986	0.9841
Male	0.9986		p=0.0000
Female	0.9841	p=0.0000	

FMR ≤ 0.1

		Male	Female
	p-AUC	0.0996	0.0972
Male	0.0996		p=0.0000
Female	0.0972	p=0.0000	

For Camera A, performance for men is significantly better than for women





Gender – Camera B

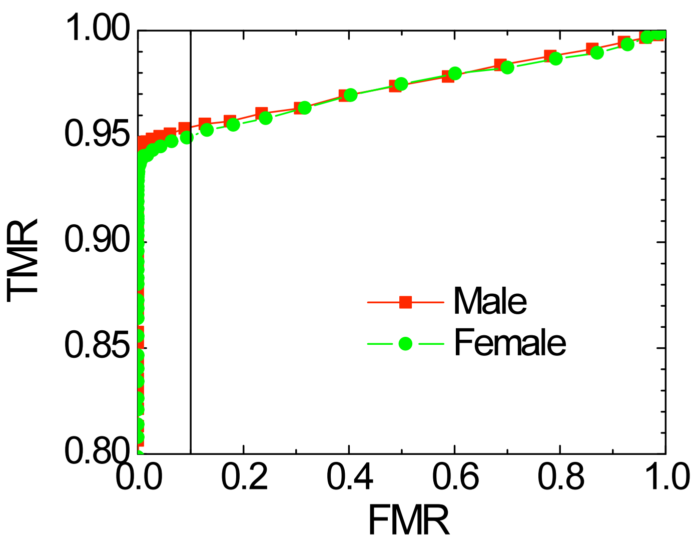
FMR ≤ 1.0

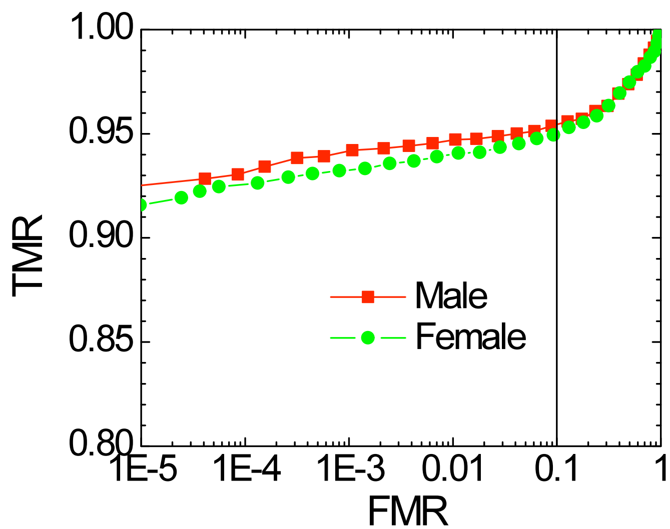
		Male	Female
	AUC	0.9742	0.9722
Male	0.9742		← p=0.5945
Female	0.9722	↑ p=0.5945	

FMR ≤ 0.1

		Male	Female
	p-AUC	0.0950	0.0945
Male	0.0950		← p=0.2421
Female	0.0945	↑ p=0.2421	

For Camera B, there is no significant performance difference between men and women





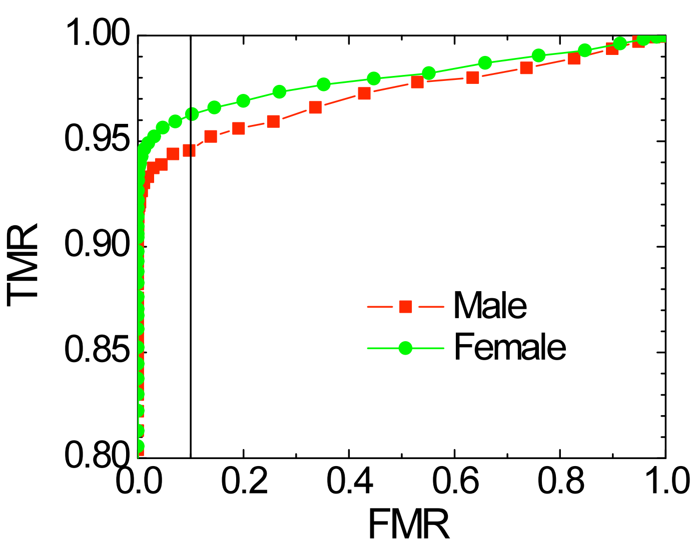
Gender – Camera C

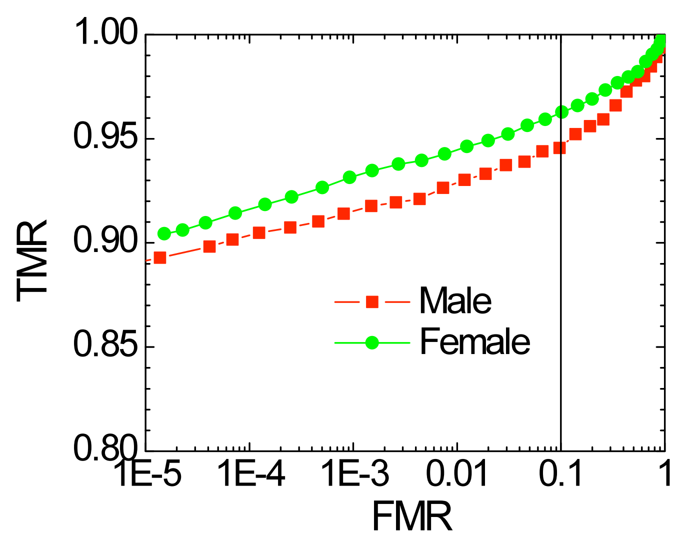
FMR ≤ 1.0

	Male	Female
AUC	0.9723	0.9797
Male 0.9723		↑ p=0.0276
Female 0.9797	← p=0.0276	

FMR ≤ 0.1

	Male	Female
p-AUC	0.0938	0.0954
Male 0.0938		↑ p=0.0001
Female 0.0954	← p=0.0001	





For Camera C, performance for women is
significantly better than for men

AUC and p-AUC figures of merit reveal performance variations between covariates

In this example:

- If population is predominantly male, use Camera A
- If population is predominantly female, use Camera C
- Can investigate origin of performance differences

Eye – Cameras A, B & C Combined

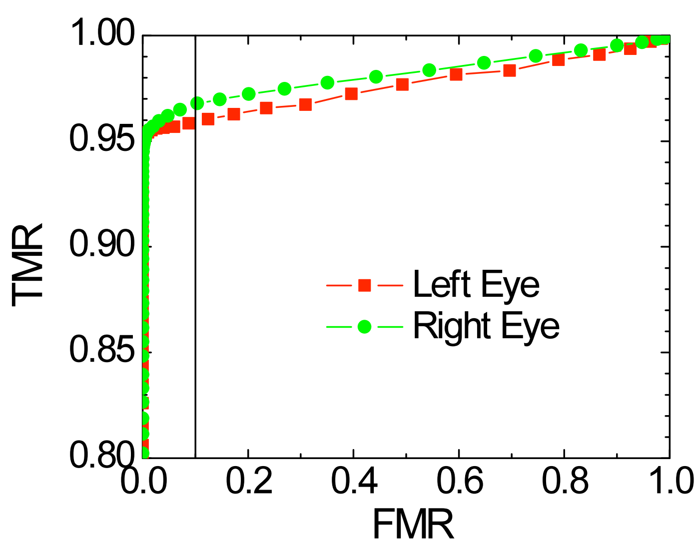
FMR ≤ 1.0

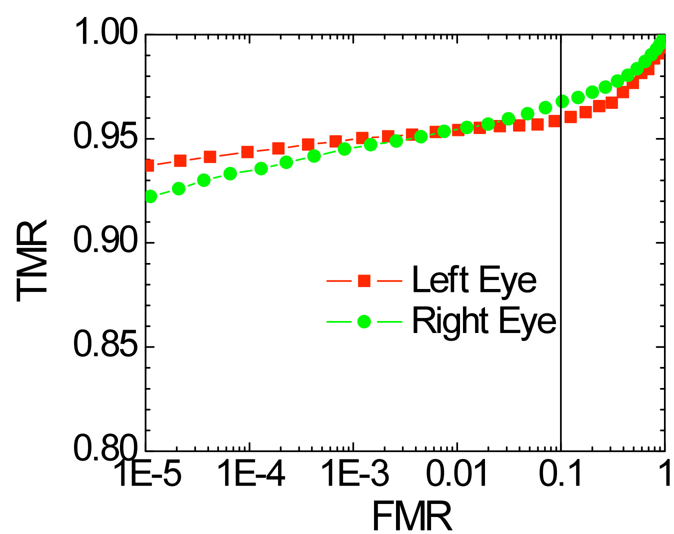
	AUC	Left	Right
	AUC	0.9776	0.9815
Left	0.9776		↑ p=0.0408
Right	0.9815	← p=0.0408	

FMR ≤ 0.1

	p-AUC	Left	Right
	p-AUC	0.0955	0.0961
Left	0.0955		↑ p=0.0059
Right	0.0961	← p=0.0059	

For Cameras A, B & C combined, performance for right eyes is significantly better than for left eyes





Eye – Camera A

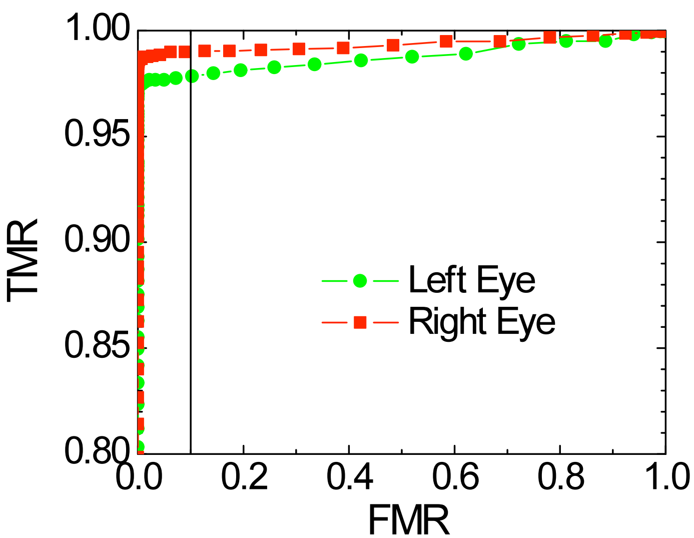
FMR ≤ 1.0

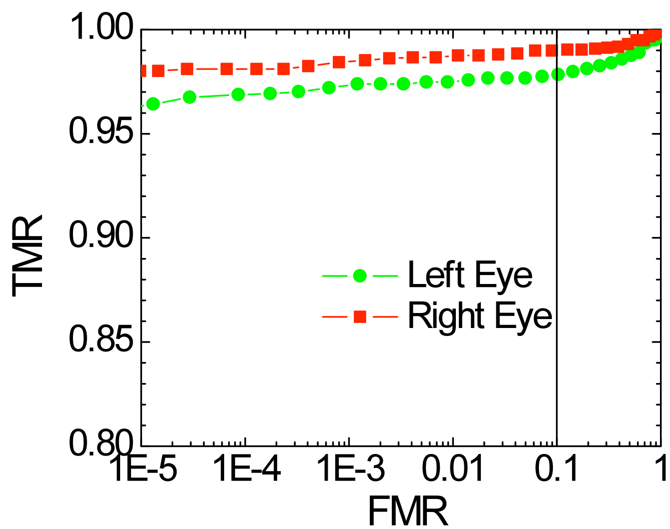
		Left	Right
	AUC	0.9875	0.9936
Left	0.9875		↑ p=0.0127
Right	0.9936	← p=0.0127	

FMR ≤ 0.1

		Left	Right
	p-AUC	0.0977	0.0989
Left	0.0977		↑ p=0.0000
Right	0.0989	← p=0.0000	

For Camera A, performance for right eyes is significantly better than for left eyes





Eye – Camera B

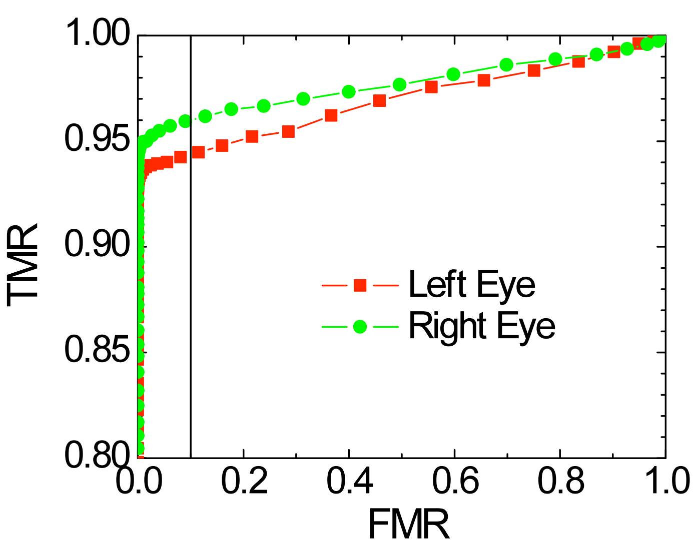
FMR ≤ 1.0

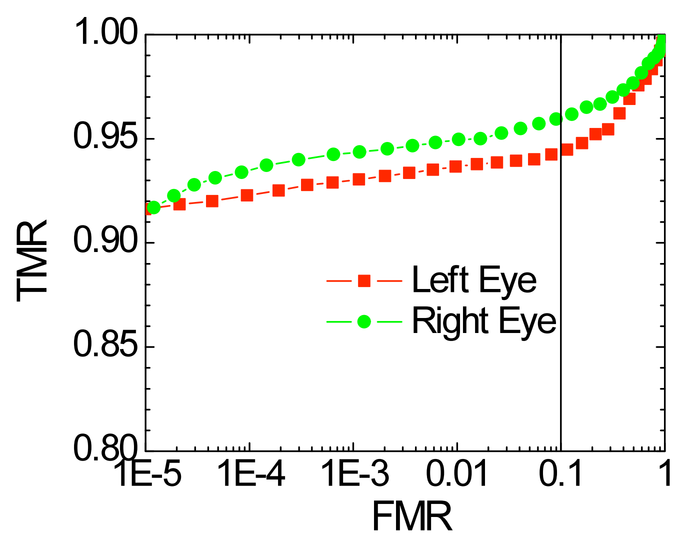
		Left	Right
	AUC	0.9692	0.9766
Left	0.9692		p=0.0439
Right	0.9766	p=0.0439	

FMR ≤ 0.1

		Left	Right
	p-AUC	0.0940	0.0955
Left	0.0940		p=0.0007
Right	0.0955	p=0.0007	

For Camera B, performance for right eyes is significantly better than for left eyes





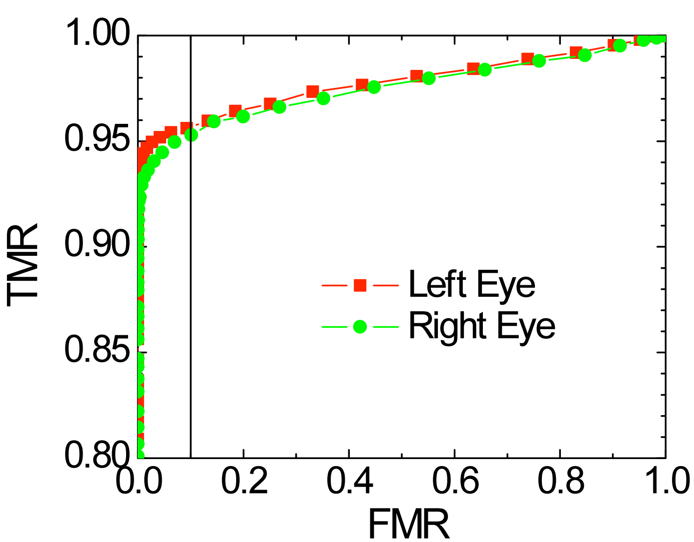
Eye – Camera C

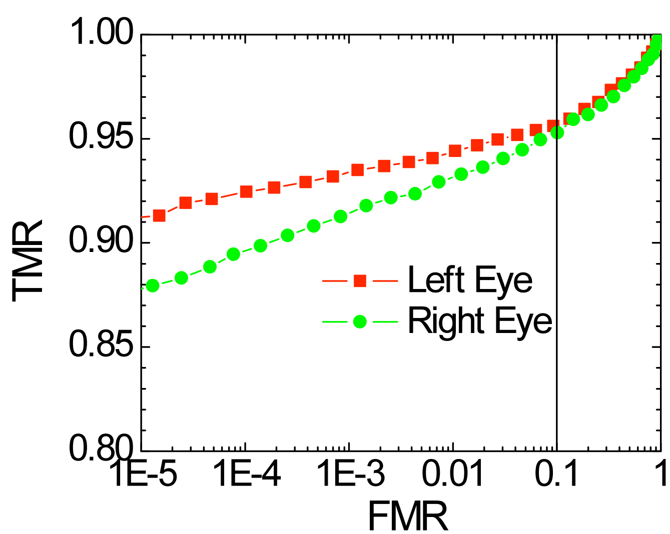
FMR ≤ 1.0

		Left	Right
	AUC	0.9778	0.9751
Left	0.9778		p=0.4259
Right	0.9751	p=0.4259	

FMR ≤ 0.1

		Left	Right
	p-AUC	0.0952	0.0942
Left	0.0952		p=0.0187
Right	0.0942	p=0.0187	





For Camera C, statistical significance is different for full AUC (FMR=1.0) and p-AUC (FMR=0.1)

- For full AUC there is no significant performance difference between left and right eyes
- For p-AUC, performance for left eyes is significantly better than for right eyes

p-AUC figure of merit reveals statistical significance for operational region of interest

In general, better to use p-AUC than AUC

Conclusions (1 of 2)

- Covariate analysis is an important tool for understanding the influence of various factors (covariates) and for enhancing the performance of biometric recognition systems
  - Identify which covariates matter and quantify how they affect performance for situations of interest
  - Useful to algorithm and hardware system developers
    - Facilitate system designs that are less sensitive or insensitive to significant covariates
  - Useful to system integrators
    - Implement systems to minimize influence of significant covariates
- Area Under Curve (AUC)-based covariate analysis approach is simple and fast to perform and easy to understand
  - AUC represents overall probability of a correct answer
  - Currently used in medical imaging field
  - System performance characterized with a single, threshold-independent metric
  - Re-sampling techniques not used
  - Produces unbiased estimates of components of variance
  - No modeling required, no parameters to tune

Conclusions (2 of 2)

- We propose a new metric, partial AUC (p-AUC), which is limited to an operationally-feasible portion of the ROC curve
- AUC and p-AUC are measures that give the probability of a correct decision when presented with both an impostor and a genuine image
- Statistical significance easy to determine using Wilcoxon p-values
  - Distribution of AUCs determines statistical significance of results
  - Small p-value indicates a significant difference between the metrics
- We have demonstrated the utility of AUC & p-AUC metrics and the Wilcoxon signed-rank statistical hypothesis test for performing covariate analyses using iris recognition data
  - The approach is effective, informative, straightforward and easy
  - Open-source code available for AUC
  - http://www.radiology.arizona.edu/CGRI/IQ/page2/page7/page7.html

Valorie S. Valencia, PhD

AUTHENTI-CORP

. . . providing scientific research, consulting, and evaluation services in all areas of authentication

PO Box 51675
Phoenix, Arizona 85076 USA
480-889-6444 office
602-432-0567 mobile
valorie@authenti-corp.com
www.authenti-corp.com

College of Optical Sciences
THE UNIVERSITY OF ARIZONA®
Frontiers of Biometrics Research

Meinel Building
1630 E. University Blvd
Tucson, AZ 85721-0094 USA
520-626-0155
valorie@optics.arizona.edu
www.optics.arizona.edu

Two-Reader Variance

$$\sigma^2 = \frac{\alpha_1}{N_{gen}} + \frac{\alpha_2}{N_{imp}} + \frac{\alpha_3}{N_{gen}N_{imp}} + \frac{\alpha_4}{2} + \frac{\alpha_5}{2N_{gen}} + \frac{\alpha_6}{2N_{imp}} + \frac{\alpha_7}{2N_{gen}N_{imp}}$$

$$\sigma_{12} = \frac{\alpha_5}{2N_{gen}} + \frac{\alpha_6}{2N_{imp}} + \frac{\alpha_7}{2N_{gen}N_{imp}}$$